ANNENBERG
BROWN UNIVERSITY

EdWorkingPaper No. 21-495

Do Refugee Students Affect the Academic Achievement of Peers? Evidence from a Large Urban School District

Camila Morales
The University of Texas at Dallas

Policy debate on refugee resettlement focuses on perceived adverse effects on local communities, with sparse credible evidence to ascertain its impact. This paper examines whether attending school with refugees affects the academic outcomes of non-refugee students. Leveraging variation in the share of refugees within schools and across grades, I find that increasing the share of grade-level refugees by 1 pp results in a 0.01 sd increase in average math scores. While I find no effect on average English Language Arts scores, using nonlinear-in-means specifications I estimate negative spillovers in ELA performance among low-achieving students and positive spillovers among high-achieving students.

VERSION: November 2021

Suggested citation: Morales, Camila . (2021). Do Refugee Students Affect the Academic Achievement of Peers? Evidence from a Large Urban School District. (EdWorkingPaper: 21-495). Retrieved from Annenberg Institute at Brown University: https://-doi.org/10.26300/p6bc-1q62

Do Refugee Students Affect the Academic Achievement of Peers? Evidence from a Large Urban School District*

Camila Morales+

Abstract:

Policy debate on refugee resettlement focuses on perceived adverse effects on local communities, with sparse credible evidence to ascertain its impact. This paper examines whether attending school with refugees affects the academic outcomes of non-refugee students. Leveraging variation in the share of refugees within schools and across grades, I find that increasing the share of grade-level refugees by 1 pp results in a 0.01 sd increase in average math scores. While I find no effect on average English Language Arts scores, using nonlinear-in-means specifications I estimate negative spillovers in ELA performance among low-achieving students and positive spillovers among high-achieving students.

Keywords: Peer effects, refugees, refugee resettlement, English learners

JEL Codes: I21, J15

October 2021

---

* The author would like to thank Tim Sass, Daniel Kreisman, Thomas Mroz, Ross Rubenstein, Catalina Amuedo-Dorantes, Joaquin Rubalcaba, Kalena Cortes, and Umut Özek for their generous feedback. Thank you also to participants at the 2019 AEFP Annual Conference, the 2019 WEAI Meetings, the 2019 AEA Summer Mentoring Pipeline Conference, and the 2019 APPAM Annual Conference. The contents of this paper use data provided by the Metro Atlanta Policy Lab for Education (MAPLE). However, all opinions are those of the author and do not represent the opinions of any partner agencies or school districts. The author acknowledges support from the National Science Foundation and the AEA Mentoring Program (NSF Award 1730651).
+ Economics Program, The University of Texas at Dallas. Email: camila.morales@utdallas.edu.

1. Introduction

The number of refugees and individuals displaced by conflict is at a historical record high. By 2019, nearly 80 million people have forcefully fled their country of origin for fear of violence, war, or persecution – a notable increase from approximately 16 million in 2005 (UNHCR, 2020).[1] Historically, the United States has taken in more refugees than any other country; however, changes in the refugee admissions ceiling for 2017 resulted in fewer refugees resettling in the US than the rest of the world for the first time since the creation of the Refugee Resettlement Program in 1980 (Connor and Krogstad, 2018)..[2] The policy debate on the cap in annual refugee arrivals is largely driven by the perceived adverse effects of resettlement on local communities, and costs that refugees may impose on all levels of government and the native population.[3] However, there is sparse credible evidence to ascertain the impact of refugees on local communities. To fill this void, I present evidence on the impact of refugee integration in public schools.

In this paper, I estimate the causal effect of a change in the share of refugee students in a grade on the academic outcomes of non-refugees. Following the literature on immigrant peer effects, I estimate refugee peer effects using cross-cohort variation in the concentration of refugees within schools and across grades. That is, confounding effects of selection into schools, and endogenous classroom formation and teacher assignments are eliminated by comparing student outcomes across grade levels within the same school and defining the peer group at the

[1] Displaced persons include refugees, asylees, and internally displaced individuals. Refugees are persons who have been forced to flee their home country due to persecution, war, or violence for reasons of race, religion, nationality, political opinion, or membership to a particular social group (UNHCR, 2020).
[2] Further restrictions to refugee resettlement have continued to take place since. For example, the Refugee Resettlement Program was suspended for 120 days in 2017 (Fix et al., 2017) and the proposed ceiling for FY2020, 18,000 individuals, was the lowest ever recorded.
[3] Concerns at the local level appear to be on the rise, as reflected in the recent Executive Order #13888 by which state and local governments must consent to resettlements before any refugees arrive in a city.

grade level. In sum, I leverage variation in the proportion of refugees in a grade and school driven by changes in the flow and age distribution of refugee arrival cohorts.

I utilize individual-level administrative data of students in grades 3 through 8 who were enrolled in public schools in the district with the highest inflow of refugees in Georgia between 2008 and 2017. Access to these records allows me to observe students' academic outcomes and rich demographic information. I complement these data with admissions records from the district's International Welcome Center containing information on students' self-reported refugee status and date of entry to the United States. My work is the first to utilize US school administrative data containing students' immigration-related information, allowing for a clear distinction between refugees and economic migrants, and analyses of refugee peer effects by length of stay.[4,5]

Results from my preferred specification show that increasing the grade-level share of refugees by one percentage point results in a 0.01 standard deviation increase in average math test scores among non-refugees. The magnitude of the spillover in average math test scores corresponds to roughly one-tenth of the impact of a highly effective teacher (Aaronson et al., 2007; Rivkin et al., 2005; Rockoff, 2004) and it is comparable, albeit smaller, to estimates from recent studies documenting positive immigrant peer effects (Figlio et al., 2021).[6]

Refugee peer effects on math test scores are higher among high-performing students and those in middle school grades. Additional analyses indicate that these positive spillover effects are driven by refugees who are classified as English Learners (ELs) and those recently arrived in

[4] To my knowledge, Green and Iversen (2020) is the only other paper to directly identify refugee students from Norwegian school administrative data.
[5] The UN defines refugees as persons who have been forced to flee their home country because of persecution, war, or violence. In contrast, immigrants are commonly considered to be persons who voluntarily leave their home country in search of better opportunities, primarily economic opportunities (Cortes, 2004).
[6] Figlio et al. (2021) find that moving from the 10th to the 90th percentile in the distribution of cumulative exposure to foreign born students (1% to 13%) increase math scores by 0.027 sd.

the country. These results provide suggestive evidence that changes in classroom resources tied to ELs (e.g., additional teachers or smaller class sizes) and access to academic support programs available to refugees who recently arrived in the country may be driving the positive spillovers in math performance.[7]

I do not find evidence of refugee peer effects on average English Language Arts (ELA) test scores among non-refugees. The estimates from my preferred specification are precise enough to rule out negative impacts larger than 0.005 standard deviations resulting from a 1 percentage point increase in the share of refugees. However, results from nonlinear specifications by non-refugees' initial achievement show significant negative spillovers in ELA scores among low-achieving students and positive spillovers among high-achieving students. These results provide suggestive evidence of possible competition over teacher time and resources between low-achieving peers and refugees.

I make two major contributions to the literature on the effects of foreign-born students on the academic outcomes of natives.[8] First, I extend this literature by presenting first evidence on

[7] The role of compensatory funding available to schools that serve refugees is a unique mechanism absent in the school integration of other foreign-born students – a distinction highlighted by prior work which finds negative immigrant peer effects (e.g., Özek, 2021, and Green and Iversen, 2020).

[8] Most research in this area focuses on the peer effects of immigrant students, failing to distinguish between economic migrants and refugees. Studies find mixed evidence with some showing that an increase in the proportion of immigrant students has a positive or null effect on the educational outcomes of peers (Conger, 2015; Figlio et al., 2021; Hunt, 2017; Jackson, 2015; Schwartz and Stiefel, 2011) and others finding negative spillovers (Brunello and Rocco, 2013; Frattini and Meschi, 2017; Gould et al., 2009; Jensen and Rasmussen, 2011). There is a related strand of literature that studies the impact of immigrant concentration on native flight. Research finds that an increase in immigrants leads to an increase in private school enrollment among native-born students (Betts and Fairlie, 2003; Cascio and Lewis, 2012; Murray, 2016; Tumen, 2019). The substantial literature on immigrant peer effects may not translate to the unique context of refugees. Apart from differences in the nature of their migration (voluntary vs. forced), we can expect differences in immigrant and refugee peer effects for three specific reasons. First, due to their unplanned and traumatic displacement, refugee students are more prone to involuntary gaps in education and are likely to experience acute emotional and psychological distress as a result of their past circumstances (Fazel et al., 2012). Both of these characteristics have implications for the academic achievement and behavior or refugee students, which can also affect their peers. Second, in contrast to low-income voluntary migrants, refugee families have access to a host of services upon arrival to the US, which can ease their integration process. Third, public school districts that receive a large inflow of refugee students qualify to receive additional federal funding through the Refugee School Impact Grant to provide support for refugee students and families. In light of these differences, it is conceivable that the peer effects associated with refugee students can differ from previous immigrant studies.

the peer effects of a diverse and contemporary sample of political refugees resettled in the US. My research complements concurrent work by van der Werf (2021) who examines the impact of the historical resettlement of Indochinese refugees who arrived in the US at the end of the Vietnam War. Results from this analysis show precise zero or small positive effects on educational achievement and attainment among natives. My work differs from van der Werf (2021) in the use of a contemporary sample of refugees and access to school administrative data. The latter enables me to identify refugee students at the grade-school level, rather than aggregate counts by county. Moreover, my work examines the spillover effects of the resettlement of refugee children, specifically. As of 2019, children make up over 43 percent of all refugees resettled in the United States (Baugh, 2020), making education a critical context in which to study the impact of refugee resettlement on host communities.

Also related to my research, recent work by Figlio and Özek (2019) and Özek (2021) use administrative data from Florida public schools to study the academic impact of inflows of environmental immigrants suddenly displaced by natural disasters in Haiti and Puerto Rico, respectively. Figlio and Özek (2019) estimate precise null peer effects on achievement and disciplinary incidents among incumbent students. In contrast, Özek (2021) finds adverse effects up to two years following the inflow of Puerto Rican migrants. Similarly, Green and Iversen (2020) estimate adverse refugee peer effects using administrative data from Norwegian schools. Both Özek (2021) and Green and Iversen (2020) point to the lack of compensatory resource allocation in schools as a possible driver of the estimated negative peer effects. Notably, my work provides new knowledge on the spillover effects of refugee resettlement in the presence of

---

Therefore, my paper contributes to the literature on immigrant peer effects by studying refugees as a unique group of foreign-born students.

compensatory financial support for schools, a federal response that is unique to political refugees.

My second contribution is to improve on the quality of data used to distinguish refugees from economic migrants. Most research on the impact of foreign-born students, specifically, and individuals, more broadly, pool together immigrants and refugees due to data limitations. To circumvent the lack of disaggregation by migration status, work focusing on refugees and the impact of resettlement relies on individuals' country of birth and year of arrival matched to data on aggregate refugee arrivals by country of origin to proxy for refugee status (Capps et al., 2015; Cortes, 2004; Evans and Fitzgerald, 2017; LoPalo, 2019).[9] In contrast, I use data on students' self-reported refugee status and year of arrival to the United States, which allow me to directly identify refugees from the foreign-born students in the sample.[10] This unique information enables me to have a more precise count of refugee students and provide first evidence on the differences in refugee peer effects by length of stay.

The remainder of the paper is organized as follows. Section 2 presents background information on the institutional characteristics of the resettlement process and describes the refugee population in Georgia. Section 3 describes the data and provides summary statistics. Section 4 outlines the empirical approach. Section 5 discusses the results and potential mechanisms. Section 6 concludes.

2. Institutional Background

2.1 The US Refugee Resettlement Process and Integration Programs for Children

Refugees who are recommended for resettlement in the United States go through a

[9] Beaman (2012) relies on data from refugee-serving organization thus allowing for direct identification of refugees.
[10] See Appendix B for a comparison between the self-reported refugee data and the proxy approach.

lengthy screening process that can take 18-24 months and includes health and security checks (Capps and Fix, 2015). The Department of Homeland Security reviews and clears applicants for admission into the country. Thereafter, one of nine national nonprofit resettlement agencies becomes responsible for individual cases, including the choice of final destination state, initial reception, and orientation.[11] Refugees with family ties in the country are commonly placed near their relatives. However, the destination decision for "free cases" is based on the characteristics of the refugee (e.g., age and health) and the availability of local resources (e.g., job and education opportunities) (Fix et al., 2017). Refugees are resettled throughout the country, with more than half concentrated in the top ten receiving states.[12]

A stated goal of the Office of Refugee Resettlement (ORR) is to provide resources and assistance that can aid in the full integration of refugees into American society. These efforts are largely implemented by extending access to an array of services that facilitate economic self-sufficiency. For example, refugees are eligible to enroll in public assistance programs such as Temporary Assistance for Needy Families, Medicaid, and the Supplemental Nutrition Assistance Program.[13] ORR also supports funding for programs aimed at the integration of refugee children by offering grants specifically designed to assist regions with a high concentration of refugee children in public schools.[14] The Refugee School Impact Grant (RSIG) funds activities that promote the academic achievement of refugees, facilitate social integration, and assist in capacity

[11] As of 2019, the nine agencies include: Church World Service, Ethiopian Community Development Council, Episcopal Migration Ministries, Hebrew Immigrant Aid Society, International Rescue Committee, US Committee for Refugees and Immigrants, Lutheran Immigration and Refugee Services, United States Conference of Catholic Bishops, and World Relief Corporation.
[12] The top 10 receiving states are: Texas, New York, Florida, Washington, Minnesota, Arizona, Michigan, Georgia, and Pennsylvania.
[13] Refugees initially qualify for most means-tested Federal public assistance programs up to 5 or 7 years. Thereafter, eligibility varies by state (Fix et al., 2017).
[14] https://www.acf.hhs.gov/orr/programs/school-impact

development for school districts serving refugees. Programs include after-school tutoring, summer activities, and interpreter services. States with more than 50 school-aged arrivals during the two years preceding a funding request qualify for the grant. In 2018, ORR awarded RSIG funding to 44 grantees totaling $14.6 million (Office of Refugee Resettlement, 2018).

2.2 Refugees in Georgia

In this study, I focus on the refugee population in Georgia - a state that has taken in over 37,000 refugees from 2002 to 2018 and ranks among the top ten resettlement states in the country. There has been substantial variation in the annual arrival of refugees over time, and this trend closely mirrors the national pattern in arrivals. As seen in Figure 1, there was an overall steady increase in refugee arrivals from 2002 up to 2016, at which point there was a sharp decline in refugee resettlement flows. In fact, the total refugee arrivals to Georgia in 2018, roughly 900, was the lowest in over a decade. The overwhelming majority of refugees are resettled in counties within the Atlanta metropolitan area,[15] with the top resettlement county comprising over 80 percent of the total refugee population in the state.[16] For this analysis, I use data from the school district that serves students living in the top refugee-resettlement county in Georgia and leverage variation in refugee arrivals from 2008-2017.

The refugee population in Georgia is comparable to that across the US in both age and countries of origin. For example, in 2014, refugees ages 18 and under made up roughly 35 percent of all arrivals to the US and 40 percent of arrivals to Georgia (Mossaad, 2016). Similarly, over one-third of Georgia refugees are from Myanmar (Burma), followed by the Democratic Republic of Congo, and Bhutan. All of these countries are among the top five countries of origin

[15] There is also a growing refugee population in the Savannah-Metro area.
[16] The refugee arrival trends for the top resettlement county follows the state trend closely, with some exceptions in the latter years. As seen in Figure A1 in the appendix, resettlements to the City of Atlanta exceeded those in the top resettlement county starting from 2014.

for refugee arrivals to the U.S. in 2015 (Mossaad, 2019). In sum, Georgia has a high share of refugee arrivals over time, with heterogeneity in refugee composition by country of origin, and it is closely representative of the refugee population in the United States. Thus, I conclude that the context in Georgia is generalizable, and results here may be useful for other traditional refugee resettlement states.

Refugee children who resettle in Georgia receive academic support services and access to integration programs financed by federal RSIG grants. From 2007-2018, the Georgia Department of Human Services was awarded a total of 6.6 million to fund after school programs and assist in capacity development for school districts serving refugees (Office of Refugee Resettlement, 2021). These services are provided either directly by local education agencies or in partnership with local refugee-serving organizations. I provide evidence on the peer effects of refugee students in light of access to a diverse range of academic services and compensatory funding for schools. Thus, part of the estimated impact can be driven by spillovers of a change in funding for support programs, which would not be available in the absence of refugee students. This is a possible mediating factor, and results may differ in the absence of such services. However, given that educational support services for refugee children is a common feature of traditional refugee-hosting communities in the US – as evidenced by the number of RSIG grantees – I do not view this as a major threat to the external validity of my results.

3. Data and Descriptive Statistics

3.1 Data

I utilize individual-level administrative data on the universe of students in grades 3 through 8 who attended public schools between 2008 and 2017 in the district with the highest inflow of refugees in Georgia.[17] I obtain information on End-Of-Grade exam scores for math and English Language Arts (ELA), student attendance, disciplinary incidents, a host of demographic characteristics (e.g., race\ethnicity, gender, and country of birth), and indicators for participation in special education programs, English as a Second Language (ESL) programs, and whether students are eligible to receive Free or Reduced-Price Lunch (FRL).

The primary variable of interest, the share of refugee students, is the number of refugees divided by the total number of students in each school-grade-year combination.[18] In order to generate this variable, it is obviously necessary to identify refugee students in the sample. As previously mentioned, refugees are commonly indistinguishable from the foreign-born in most data sets, including school administrative records. I circumvent this issue by obtaining access to school registration records from the district's International Welcome Center, which contain information on students' self-reported refugee status and date of arrival to the United States. [19] These unique records allow me to directly identify refugees from the sample and clearly distinguish them from other foreign-born students. These data also enable me to estimate refugee peer effects by length of stay.

While information on refugee status is self-reported, there are various reasons that validate its credibility. First, unlike undocumented migrants, refugee families have little incentive to withhold immigration-related information given their legal status. Second, refugee status is informally verified by school administrators using students' immigration documents as a

[17] I denote years by the end of the Spring semester, such that 2008 refers to the school year 2007-2008. I access the data from the Metro Atlanta Policy Lab for Education (MAPLE).
[18] Students are assigned to the school with the longest enrollment. It may or may not be the same school that students attend at the time of the test.
[19] The sample district does not track students' immigration status. It only allows for self-reported identification of refugee students in order to target programs and services to this population.

form of identification at the time of registration.[20] Third, it is common for staff of refugee-serving organizations to accompany recently arrived refugees at the time of registration and encourage parents to provide this information. Lastly, schools encourage self-identification of refugees in order to target programs and services to this community. In sum, I reasonably conclude that self-reported information on refugee status accurately captures the refugee student population in the district.

While refugee self-identification is my preferred measure and the one used in the analysis, I also explore a second strategy commonly employed in the literature (see Cortes 2004, Capps et al. 2015, and Evans and Fitzgerald 2017) that proxies for refugee status using country of birth and year of arrival. Notably, I do not find evidence of negative refugee peer effects on average achievement irrespective of the approach to identify refugees in the data. Appendix B provides more information comparing results between methodologies.

3.2 Descriptive Statistics

Refugee students make up roughly 3 percent of all student-year observations in the sample. Out of 124 elementary and middle schools, 109 (88 percent) enrolled at least one refugee student during the school years 2008-2017, and in 21 schools (17 percent), refugees make up over one percent of students. Henceforth, the latter will be referred to as high refugee-concentration schools.[21] Among refugee-serving schools, there is an average of five refugee students per grade or 2 percent of total enrollment; these increase to an average of 24 refugees per grade or 11 percent of total enrollment among high refugee-concentration schools. As seen in

[20] In conversations with education program coordinators from several refugee resettlement agencies, I learned that most refugees only have their I-94 as their identification document at the time of school registration. Therefore, while the school does not ask for this form during the registration process, refugee parents end up using it to enroll their kids in school and hence it is used to informally verify that students are in fact refugees.
[21] Refugee school type is a time-invariant measure that classifies schools by their mean share of refugee students across all grades.

Figure 2, most schools have significant variation in the share of refugee students across grades.[22] Lastly, students in refugee-serving schools are similar across several observable characteristics to students in schools that never enroll refugees. For example, while refugee-serving schools have a higher share of students that qualify for FRL, the difference compared to schools with no refugees is, on average, trivial.[23]

Table 1 reports summary statistics for the students in the sample, stratified by nativity status – U.S-born, immigrant, and refugee. On average, students in the district score below the state mean in both ELA and math, with refugee students having substantially lower test scores. [24] Refugee students, on average, score 1.25 standard deviations below the state mean in ELA, compared to 0.21 and 0.33 standard deviations for US-born and immigrant students, respectively. The pattern for math test scores across groups is similar, although group differences are smaller. Specifically, refugee students score 0.93 standard deviations below the state average, compared to 0.27 and 0.21 standard deviations for US-born and immigrant students, respectively.

Refugee students attend school fewer days per school year compared to both US-born and immigrant students – this is expected given that refugees can be resettled in the United States at any point during the school year. However, there is no substantial difference in the share of days absent across groups – on average, students in the sample miss school 3 percent of the total days they are enrolled. In contrast, there are noticeable differences in disciplinary incidents across groups. Compared to both US-born and immigrant students, refugee students have fewer

[22] Results are robust to dropping the school with the highest variation in the share of refugee students across grades.
[23] Table A.1 shows summary statistics of all non-refugee students across school types. Column (1) presents summary statistics for students in schools where no refugee student was ever enrolled. Columns (2) and (3) show summary statistics for non-refugee students enrolled in refugee-serving schools and the set of schools with a concentration of refugees above 1 percent.
[24] Immigrant and refugee students are classified to be mutually exclusive. Immigrants denote all foreign-born students who do not self-identify as refugees.

disciplinary incidents and are less likely to be involved in disciplinary infractions that lead to school suspensions.

Refugees make up a diverse student group and are likely to live in low-income households. On average, 62 percent of refugees are Asian and 30 percent are Black, 89 percent qualify for FRL, and 84 percent receive English as a Second Language (ESL) services. The peers of refugees are also likely to live in low-income households – 71 percent of US-born and 79 percent of immigrant students qualify for FRL. On average, 73 percent of US-born students in the district are Black and 9 percent receive Special Education services. On the other hand, 44 percent of immigrant students are Hispanic, and 42 percent receive ESL services.

4. Empirical Strategy

There are three main issues concerning the empirical estimation of peer effects.[25] First, there is simultaneity of outcomes, known as the reflection problem, in which own performance impacts peer performance and simultaneously reflects on own achievement (Manski, 1993). Second, individuals in a group tend to be exposed to common inputs, such as sharing the same teacher, thereby impeding the causal identification of peer effects apart from unobserved correlated factors. Third, in the absence of randomization, group formation is endogenous. In light of these challenges, estimating a naïve peer effects regression would lead to biased estimates.

In the context of this paper, correlated inputs and endogenous group formation are of most concern. First, refugee students are not randomly assigned to schools. Therefore, peer selection is endogenous inasmuch as parents make school decisions based on the demographic or socioeconomic composition of the student body. Failure to control for this mechanism would

[25] See Epple and Romano (2011) and Moffitt (2004) for thorough theoretical and empirical reviews of the peer effects literature.

confound effects driven by school quality. Second, teachers and students are typically not randomly assigned to classrooms. To the extent that there is systematic teacher-student matching as a function of unobserved characteristics that are correlated with the outcomes of interest, failure to account for this confounding factor would not allow for the isolation of peer effects from the impact of teacher quality.

Following the literature on immigrant peer effects, I estimate refugee peer effects using cohort variation in the concentration of refugees within schools and across grades. That is, any confounding effects of school selection are eliminated by comparing students within the same school, and the consequences of endogenous teacher assignment are mitigated by measuring peers at the grade, not the classroom level.[26]

4.1 Reduced-Form, Linear-in-Means Peer Effects

I specify a reduced-form regression to estimate the effect of a change in the proportion of refugee students at the school-grade-year level on a host of student-level outcomes. Equation 1 represents the preferred regression specification:

$$A_{igst} = \beta_o + \beta_1 \left(\frac{Refugee_{gst}}{N_{gst}} \right) + \beta_2 A_{it-1} + X'_{it}\gamma + \lambda_{st} + \mu_g + \varepsilon_{igst} \tag{1}$$

where A_{igst} is an outcome measure for non-refugee student i in grade g at school s in year t; A_{it-1} is the same outcome in year $t-1$; X_{it} is a vector of individual time-varying characteristics; λ_{st} is a vector of school-by-year fixed effects to account for time-varying school characteristics that can drive changes in the share of refugees and student outcomes (e.g.,

[26] Evidence suggests that classroom peer effects are stronger than grade-level effects (Burke and Sass, 2013). Thus, by measuring peer effects at the grade-level, my estimates are likely biased toward zero.

changes in school leadership); μ_g is a vector of grade fixed effects controlling for grade-level differences in student outcomes; and ε_{igst} is an idiosyncratic error term.

I estimate equation (1) using as outcome variables ELA and math test scores normalized with respect to the state test score distribution by grade-year-subject.[27] In addition, I run separate regressions to disentangle the peer effect across different categories of non-refugee peers, namely US-born and immigrant students. I do this to investigate whether there are differential effects possibly driven by differences in mechanisms. For example, it is likely that immigrant and refugee students compete for the same classroom resources (e.g., language support from the teacher) such that an increase in refugee concentration can lead to negative spillover effects among immigrant students.[28]

The main variable of interest, $\left(\frac{Refugee_{gst}}{N_{gst}}\right)$, is the share of refugee students in a particular grade, school, and year, where N_{gst} is the total number of students. This variable captures the concentration of refugees at the grade level to which a non-refugee student is exposed. The coefficient β_1 measures the refugee peer effect. The main source of identifying variation is intertemporal changes in the proportion of refugee students in a particular grade-school-year combination. Therefore, in order to interpret β_1 as the causal effect of a change in the grade-level proportion of refugees, it must be the case that the variation in the share of refugee students (across grades within a school in a given year) is orthogonal to any unobserved variables that may affect the change in non-refugee student test scores after controlling for past achievement, time-varying school characteristics, and grade-specific differences in achievement.[29]

[27] I also estimate refugee peer effects on measures of student attendance and disciplinary incidents. Results from these analyses are available upon request.
[28] There is evidence of adverse immigrant peer effects on performance among for immigrants, particularly those of the same native country (Schneeweis, 2015).
[29] Note that by adding lagged test scores as a control variable, I account for all prior inputs that impact achievement

Given this preferred specification, threats to identification would arise from systematic variation in the share of grade-level refugees and changes in student outcomes in the same school and year. This is arguably an unlikely event, especially due to the inherent uncertainty in the proportion of refugee students in each grade within a school. The within-school temporal variation in refugee students across grades primarily depends on the change in refugee arrivals and the age composition of refugees, both of which depend on factors that are reasonably exogenous to other within-school variables affecting student performance across grades. First, annual refugee inflows are directly a function of the supply of refugees (determined by international war and conflict), annual refugee admissions ceilings determined at the federal level,[30] and service capacity of resettlement agencies in the state. Second, the share of refugees across grades depends on the age distribution of the incoming cohort of refugees, which is expected to vary independently of native students' outcomes.

A second concern for identification is the possibility of nonrandom native flight in response to refugee inflows in schools. Prior work demonstrates that US-born students are more likely to enroll in private schools or move districts in response to an increase in foreign-born students (Betts and Fairlie, 2003; Cascio and Lewis, 2012; Murray, 2016; Tumen, 2019). This is especially true of White students and those living in comparatively more affluent households. Therefore, failure to account for endogenous sorting across schools is most likely to result in a spurious negative correlation between the share of foreign-born students and native achievement, as documented in recent work by Figlio et al., (2021). To mitigate this concern, I estimate variants of equation (1) that control for school-by-grade and grade-by-year fixed effects. In these

including prior exposure to refugee students.

[30] The Refugee Act of 1980 makes explicit that the lawful entry of refugees into the country is a matter of federal, not state jurisdiction. However, recent changes by Executive Order #13888 gives state and local governments the right to consent to resettlements before any refugees are resettled in a locality (Trump, 2019).

models, endogenous sorting would have to vary across grades within a school and across years to be a threat for identification; results are robust to these changes.[31] Moreover, I conduct analyses that limit variation in the share of grade-level refugees to the inflow of same-year refugee arrivals.[32] Results from these analyses are discussed in Section 5.4.

4.2 Reduced-Form, Nonlinear-in-Means Peer Effects

Prior evidence suggests that peer effects are stronger nonlinearly with respect to initial student achievement levels (Burke and Sass 2013; Imberman, Kugler, and Sacerdote 2012). It has also been shown that teachers adjust the level at which they teach in response to changes in classroom composition (Duflo et al., 2011; Lavy and Schlosser 2011). Given that achievement among refugee students is substantially lower than that of non-refugees, it is possible that teachers allocate more time toward reviewing academic content, or slowing down the pace of instruction to accommodate their needs. If this is the case, an increase in the share of refugee students would result in a positive spillover effect among low-achieving peers who would benefit from additional review and reinforcement. On the other hand, teachers may face a tradeoff between spending more time on language support services to accommodate the needs of refugees and spending more time on reviewing core content instruction. If teachers spend more time on language support, this can lead to a decrease in the achievement of peers, especially low-achieving students. Results of the nonlinear-in-means estimations can provide evidence of whether these mechanisms are in effect.[33]

---

[31] See Table 8, columns (9)-(14).
[32] See Tale 8, columns (3)-(4).
[33] There can also be competition over teacher resources between refugees and non-refugee language learners. I estimate heterogeneous refugee peer effects by non-refugee ESL classification to investigate this potential mechanism. Results are shown in Table A.3 in the appendix.

I relax the linear-in-means assumption from equation (1) to explore these possible heterogeneities by student baseline achievement. I estimate the following specification:

$$A_{igst} = \beta_o + \beta_1 \left(\frac{Refugee_{gst}}{N_{gst}}\right) \times low_i + \beta_2 \left(\frac{Refugee_{gst}}{N_{gst}}\right) \times middle_i + \beta_3 \left(\frac{Refugee_{gst}}{N_{gst}}\right) \times high_i + \beta_4 A_{it-1} + \lambda_{st} + \mu_g + \varepsilon_{igst} \quad (2)$$

where low_i, $middle_i$, and $high_i$ are indicators of time-invariant initial achievement; and all other variables are defined as in equation (1). In particular, following Burke and Sass (2013), I assign each student's initial test performance to a low, middle, or high "type" based on whether the student's first observed test score falls in the bottom quintile, between the 20th and 80th percentiles, or the top quintile of the grade-by-year state test score distribution. Estimates of β_1, β_2, and β_3 measure refugee peer effects across students of different underlying baseline achievement.

5. Results

5.1 Linear-in-Means Refugee Peer Effects

Table 2 reports the linear-in-means estimates of refugee peer effects on ELA test scores for non-refugee students, obtained by estimating equation (1). Column (1) shows results using the full sample of non-refugee students, columns (2) and (3) present results using the subsamples of US-born and immigrant students, respectively. Panel A presents results for the full sample of refugee-serving schools, and Panel B reports results for high refugee-concentration schools. I present results by different school "types" in order to explore whether the peer effects depend on the concentration of refugees at the school level, and as a robustness check that results are driven by significant variation in the share of grade-level refugees, not idiosyncratic differences driven by a handful of students. In all specifications, standard errors are clustered at the school-grade-year level.[34]

Results in Table 2 suggest that, on average, there is no impact of refugees on non-refugee performance in ELA. The estimated coefficients are small in magnitude and none are statistically different from zero. Specifically, I estimate that increasing the share of grade-level refugees in high concentration schools by 1 percentage point is associated with a decrease in ELA test scores by 0.0003 standard deviations. The estimates from the preferred specification are precise enough to rule out negative impacts larger than 0.005 standard deviations. Thus, I conclude that changes in the proportion of grade-level refuges, whose average ELA test scores are more than one standard deviation below non-refugee students, does not have a statistically significant impact on average non-refugee ELA test scores.

Table 3 presents the linear-in-means refugee peer effects for math test scores. Unlike the effects for ELA, all of the point estimates are positive, and I find statistically significant and meaningful impacts among the subset of high refugee-concentration schools. The coefficients are modest in magnitude and increase with the school-level concentration of refugees. Specifically, I find that increasing the share of grade-level refugees by 1 percentage point in schools that serve a high proportion of refugees results in higher math scores for nonrefugee students by 0.01 standard deviations. The magnitude of the spillover in average math test scores corresponds to roughly one-tenth of the impact of a highly effective teacher (Aaronson et al., 2007; Rivkin et al., 2005; Rockoff, 2004) and it is comparable, albeit smaller, to estimates from recent studies documenting positive immigrant peer effects (Figlio et al., 2021).

[34] Results in Table A.5 in columns (1) – (4) show estimates with standard errors clustered at school and school-by-year levels.

Further analyses disaggregated by peer group nativity status and grade level show that the positive spillovers in math test scores are higher for US-born students and those in middle school grades.[35] I also run specifications that allow for non-linearities in the share of refugee students at the grade level.[36] I find small and insignificant negative spillovers in math achievement at small shares of grade-level refugees, and large positive spillovers at high shares of refugees. Specifically, for the high refugee-concentration schools, positive peer effects in math test scores are realized when refugees in a grade make up at least 1.2 percent of students.

5.2 Nonlinear-in-Means Refugee Peer Effects

The first set of results were based on the assumption that all non-refugee peers are equally impacted by the proportion of refugee students in their grade. However, prior evidence suggests that peer effects are stronger nonlinearly with respect to students' initial achievement (e.g., Burke and Sass, 2013; Frattini and Meschi, 2017). In addition, nonlinear effects can uncover mechanisms driven by changes in teacher behavior, as explained in Section 4.2. Tables 4 and 5 present results from specifications where I relax the linear-in-means assumption and estimate differential effects for non-refugee students who are initially low-, middle-, or high-achieving.

Table 4 shows the nonlinear peer effects for ELA test scores. I find differential peer effects by initial ELA achievement that suggest possible competition over teacher resources between low-achieving students and refugees.[37] Specifically, a 1 percentage point increase in the

[35] Results by grade levels are shown in Table A.4 in the Appendix.

[36] I run specifications that include the square of the share of refugees in a grade, and a separate model interacting the share of refugees in a grade with the level of refugees in a school. Tables A.6 and A.7 present results from these estimations using ELA and math test scores as outcome variables, respectively.

[37] Table A.3 in the appendix shows results of a separate specification that explores whether there are competition effects between refugees and non-refugees who receive ESL services. If there is competition over teacher resources it should be stronger among students who have similar needs, in this case language support. I find a negative relationship between the share of refugees and ELA achievement among non-refugee students who receive ESL

share of refugee students results in lower ELA scores by as much as 0.006 standard deviations for low-achieving students. On the other hand, I find positive spillover effects for high-achieving students by up to 0.01 standard deviations. Estimates are statistically significant for the pooled sample of non-refugees and the subsample of US-born students, and across all school types. I find small and insignificant effects for middling students.

Table 5 presents nonlinear-in-means results for math test scores of non-refugee students. I find positive spillovers in math scores for students across all levels of initial achievement, with large and statistically significant effects for high-achieving students, and middling students enrolled in high refugee-concentration schools. In sum, to the extent that teachers may adjust their class time allocation or core content focus, I find no evidence that refugee peers experience a decrease in math performance. This stands in contrast to the nonlinear results for ELA where I find evidence of potential competition between low-achieving students and refugees. The differences in nonlinear effects across subjects are reasonable given that average test scores differences between refugees and non-refugees are bigger for ELA, making it likely that refugees require relatively more teacher time and resources in this subject.

5.3 Additional Mechanisms

In addition to exploring competition over teacher resources and time allocation, discussed above, I examine two other mechanisms that can give rise to spillover effects driven by a change in the share of refugees. First, I explore differential refugee peer effects due to variation in the share of English Learners (ELs) in the classroom, resulting in possible changes in class size and classroom resources. Approximately 84 percent of refugee students in the sample are classified

support across all school types, with significant effects for high refugee-concentration schools. I find no differential effect in math.

as ELs; therefore, an increase in the share of refugee students also increases the proportion of ELs in a grade.

Previous research shows that having more EL peers is associated with lower test scores for non-EL students (Ahn and Jepsen, 2015; Cho, 2012; Diette and Oyelere, 2014). However, a related strand of literature suggests that effects differ by the type of English as a Second Language service provided to ELs. For example, Chin et al. (2013) find that providing bilingual education programs aimed at increasing achievement among ELs has positive spillover effects for non-EL students.[38] Thus, it is plausible that an increase in EL students, due to a higher share of refugees, has implications for non-EL students that vary with the type of ESL instruction. Consider the following two cases. If EL students are served by a "pull-out" model, thus instructed in a separate classroom during a portion of the day, a higher share of refugee students implies a temporary reduction in class size for non-refugee peers. On the other hand, if EL students are served by a "push-in" model where a co-teacher is uniquely focused on assisting ELs in the classroom, a higher share of refugee peers leads to an increase in classroom resources that allow the principal teacher to re-allocate their time and instruction to exclusively service non-refugee students. Both of these instructional models have implications that can result in positive spillovers among non-refugees; namely, a temporary reduction in class size or the presence of a co-teacher.

While I do not present results that directly disentangle these two mechanisms, I explore whether there are differential effects by refugee students' EL classification. In essence, if the mechanisms driven by English as a Second Language instruction explain the positive spillovers in average math achievement, one can expect estimates to be stronger among EL refugees.

[38] Additional evidence on the impacts of bilingual education programs (e.g. Bibler, 2020; Steele et al., 2017) suggests possible positive EL peer effects in non-traditional school settings.

Results are shown in Table 6. All of the estimated peer effect associated with the share of EL refugees are positive, and all math effects are statistically significant and larger than the average refugee peer effects reported in section 5.1. This suggests that the positive spillovers in math are possibly explained by a change in classroom resources tied to changes in the proportion of ELs in a grade. On the other hand, most of the coefficients associated with the share of non-EL refugees are negative, though all are statistically insignificant.

Second, I explore changes in access to support services aimed at refugees' academic success and overall school integration. Schools with a significant number of refugees commonly partner with refugee-serving organizations to provide academic support programs that focus on homework assistance and tutoring. Although in principle these programs are intended to serve refugee students, some of these services are also made available to non-refugees.[39] To the extent that an increase in academic support services for refugees can result in spillovers to non-refugee students, this can impact peer test scores positively. It may also be the case that these additional resources loosen schools' budget constraints, thus allowing them to provide more services to nonrefugee students. Importantly, these services are targeted to specific grades with a relatively high proportion of refugees. Therefore, access to these programs varies across grades within the same school and year. Given that these support services would not be made available in the absence of refugee students, I interpret this as part of the total spillover effect of attending school with refugees.

While I do not have data on afterschool program provision or student participation, I explore this mechanism by leveraging the fact that funding for several of these programs is tied to refugee length of stay in the country. For example, afterschool programs funded by the

[39] I obtained this information via informal interviews with school administrators and program coordinators.

Refugee School Impact Grant (RSIG) focus exclusively on refugees who have been in the country five years or less.[40] Thus, I leverage individual-level information on refugees' date of entry into the US to explore whether peer effects differ between short-term refuges, for whom schools receive compensatory funding, and long-term refugees.[41] If non-refugee students are exposed to a higher share of short-term refugees, they are more likely to have access to afterschool programs and other targeted educational support. Thus, estimates from this specification provide suggestive evidence of whether this mechanism is in effect.[42]

Table 7 presents results on the peer effects associated with short-term (up to 5 years) and long-term (6 years of more) refugees. I find that an increase in the grade-level share of short-term refugees results in higher math achievement. For example, a 1 percentage point increase in the proportion of short-term refugees in high refugee-concentration schools increases math test scores of nonrefugees by 0.013 standard deviations. I do not find statistically significant effects associated with the share of long-term refugees, or any statistically significant impacts on average ELA performance. In sum, I find evidence that an increase in the share of refugees tied to access to academic support programs have positive spillovers in math achievement for non-refugees. Notably, the role of compensatory funding available to schools that serve refugees is a unique mechanism absent in the school integration of other foreign-born students – a distinction highlighted by prior work which finds negative immigrant peer effects (e.g., Özek, 2021, and Green and Iversen, 2020).

[40] https://www.acf.hhs.gov/orr/programs/school-impact

[41] The choice to group refugees into these categories comes primarily from the differences in access to targeted educational services, but also the fact that refugees are eligible to apply for US citizenship after living in the country for five years, which can have implications on the educational achievement of refugee children (Felfe et al., 2019).

[42] I also estimate a separate specification where I identify refugees as "recently arrived" if they have been in the country for less than one year, and "settled" if they have lived in the US for one year or more to capture the immediate short-term effects of resettlement. Results are shown in Table A.1 in the appendix.

5.4 Robustness Checks

I begin by checking the sensitivity of the results to various definitions of refugee students and refugee-serving schools. Frist, some of the students who self-identify as refugees also report being born in the US. I exclude these students when I generate the share of grade-level refugee used in the main specification. In this section, I check whether results change when I count these students as “refugees”. Second, I conduct additional analyses that limit variation in the share of grade-level refugees to the inflow of same-year refugee arrivals. Third, in the main specification, I classify schools as refugee-serving if the school-wide share of refugee students is nonzero at any point during the sample period, including all grades, even those that are not used in the estimation sample.[43] I check whether results are sensitive to restricting this variable to grades 3 through 8. Fourth, I exclude from the sample the school with the highest variation in the share of grade-level refugees. With the exception of same-year refugee arrivals, the linear-in-means effects are robust to redefining refugees and refugee-serving schools. Results are shown in Table 8, columns (1) – (8).

Moreover, I estimate results controlling for school-by-grade fixed effects and grade-by-year fixed effects to account for variation in grade-level characteristics within schools and grade-level characteristics over time, respectively. I also run a specification where I control for all two-way fixed effects, that is identifying variation comes from temporal changes in the proportion of refugees within the same grade and school. As shown in Table 8 columns (9) – (14), even accounting for all these fixed effects, the conclusion remains that increasing the proportion of refugees at the grade level results in positive spillovers in math achievement.

[43] For example, I use the K-5 concentration of refugees to designate whether an elementary school serves refugees.

Lastly, I conduct three robustness checks that address issues of potential measurement error in test scores. First, in 2015 there was a change in the End-of-Grade exams, and it was reported that, as part of the transition, some districts experienced technology-related issues that led to possibly unreliable test scores.[44] I re-run the preferred specification excluding the school year 2015 to check whether the results are sensitive to this potential source of measurement error in test scores. Second, I run gains models where I assume the coefficient on lagged achievement is equal to 1 and estimate the main specification using the change in test scores as the outcome variable in order to account for possible bias from the inclusion of a lagged dependent variable, which is measured with error (Koedel et al., 2015; Sass, Semykina, and Harris 2014). Third, I estimate models where I control for both lagged test scores to mitigate the effects of measurement error (Lockwood and McCaffrey, 2014). While the coefficients estimated in these robustness checks are smaller in magnitude, they are all qualitatively similar to the main results. Results from these analyses are shown in Table A.5 in the appendix.[45]

6. Conclusion

Over the past few years, the United States has made large cuts to the number of refugees who are allowed to resettle in the country. The 2020 cap on arrivals, set at 18,000, was the lowest since the beginning of the refugee resettlement program in the 1980s. Much of the policy debate on whether to change the flow of refugee resettlement centers in part on the perceived costs that refugees may impose on local communities. While there is some research on the impact of resettlement, I present first evidence on the spillovers associated with the resettlement of refugee children within the specific context of US public schools. Using individual-level data from the

[44] See https://www.ajc.com/blog/get-schooled/testing-glitches-mean-milestones-will-not-count-for-retention/azvpotAK40vloy7ndmx5bL/

[45] Table A.5 also contains estimates checking for differences in clustering the errors.

school district with the largest refugee resettlement population in Georgia, I estimate effects on ELA and math achievement of non-refugee students resulting from increases in the share of refugees in their school and grade

I find no evidence of widespread detrimental academic effects due to an increase in the share of refugee students at the grade level. Rather, an increase in the share of refugees results in higher math test scores for non-refugee students, concentrated in schools that enroll a high proportion of refugees. I also find no impact on average ELA achievement, although there is evidence of negative spillovers among low-achieving students, which suggests possible competition over resources.

Specifically, I find that increasing the proportion of refugees by 1 percentage point (roughly half the current average share) results in higher math scores of non-refugee students by 0.01 standard deviations. The magnitude of the spillover in average math test scores is comparable, albeit smaller, to estimates from recent studies documenting positive immigrant peer effects (Figlio et al., 2021).

Heterogeneous analyses by refugees' EL classification and length of stay in the country provide suggestive evidence that the positive peer effects in math may be driven by changes in classroom resources and access to academic support programs. Schools' access to compensatory funding as a result of an inflow of foreign-born students is unique to refugee arrivals, and results suggest that additional resources more than offset possible negative spillovers. In fact, this analysis points to some positive impacts on average achievement.

References

Aaronson, D., Barrow, L., & Sander, W. (2007). Teachers and Student Achievement in the Chicago Public High Schools. *Journal of Labor Economics*, *25*(1), 95. https://doi.org/10.1086/508733

Ahn, T., & Jepsen, C. (2015). The effect of sharing a mother tongue with peers: Evidence from North Carolina middle schools. *IZA Journal of Migration*, *4*(1), 5. https://doi.org/10.1186/s40176-015-0030-2

Baugh, R. (2020). *Refugees and Asylees: 2019* (p. 10) [Annual Flow Report]. Deaprtment of Homeland Security, Office of Immigration and Statistics.

Beaman, L. (2012). Social Networks and the Dynamics of Labour Market Outcomes: Evidence from Refugees Resettled in the U.S. *The Review of Economics and Statistics*, *79*(1), 128–161.

Betts, J. R., & Fairlie, R. W. (2003). Does immigration induce 'native flight' from public schools into private schools? *Journal of Public Economics*, *87*(5), 987–1012. https://doi.org/10.1016/S0047-2727(01)00164-5

Bibler, A. (2020). Dual Language Education and Student Achievement. *Education Finance and Policy*, 1–57. https://doi.org/10.1162/edfp_a_00320

Brunello, G., & Rocco, L. (2013). The effect of immigration on the school performance of natives: Cross country evidence using PISA test scores. *Economics of Education Review*, *32*, 234–246. https://doi.org/10.1016/j.econedurev.2012.10.006

Burke, M. A., & Sass, T. R. (2013). Classroom Peer Effects and Student Achievement. *Journal of Labor Economics*, *31*(1), 51–82. https://doi.org/10.1086/666653

Capps, R., & Fix, M. (2015, October 20). *Ten Facts About U.S. Refugee Resettlement*. Migrationpolicy.Org. https://www.migrationpolicy.org/research/ten-facts-about-us-refugee-resettlement

Capps, R., Newland, K., Fratzke, S., Groves, S., Fix, M., McHugh, M., & Auclair, G. (2015). *The Integration Outcomes of U.S. Refugees: Successes and Challenges*. Migration Policy Institute. https://www.migrationpolicy.org/research/integration-outcomes-us-refugees-successes-and-challenges

Cascio, E. U., & Lewis, E. G. (2012). Cracks in the Melting Pot: Immigration, School Choice, and Segregation. *American Economic Journal: Economic Policy*, *4*(3), 91–117. https://doi.org/10.1257/pol.4.3.91

Chin, A., Daysal, N. M., & Imberman, S. A. (2013). Impact of bilingual education programs on limited English proficient students and their peers: Regression discontinuity evidence from Texas. *Journal of Public Economics*, *107*, 63–78. https://doi.org/10.1016/j.jpubeco.2013.08.008

Cho, R. M. (2012). Are there peer effects associated with having English Language Learner (ELL) classmates? Evidence from the Early Childhood Longitudinal Study Kindergarten Cohort (ECLS-K). *Economics of Education Review*, *31*(5), 629–643. https://doi.org/10.1016/j.econedurev.2012.04.006

Conger, D. (2015). Foreign-born Peers and Academic Performance. *Demography*, *52*(2), 569–592. https://doi.org/10.1007/s13524-015-0369-2

Connor, P., & Krogstad, J. M. (2018). For the first time, U.S. resettles fewer refugees than the rest of the world. *Pew Research Center*. https://www.pewresearch.org/fact-tank/2018/07/05/for-the-first-time-u-s-resettles-fewer-refugees-than-the-rest-of-the-world/

Cortes, K. E. (2004). Are Refugees Different from Economic Immigrants? Some Empirical Evidence on the Heterogeneity of Immigrant Groups in the United States. *The Review of Economics and Statistics*, *86*(2), 465–480. https://doi.org/10.1162/003465304323031058

Diette, T. M., & Oyelere, R. U. (2014). Gender and Race Heterogeneity: The Impact of Students with Limited English on Native Students' Performance. *The American Economic Review*, *104*(5), 412–417.

Duflo, E., Dupas, P., & Kremer, M. (2011). Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya. *American Economic Review*, *101*(5), 1739–1774. https://doi.org/10.1257/aer.101.5.1739

Epple, D., & Romano, R. E. (2011). Peer Effects in Education: A Survey of the Theory and Evidence. In J. Benhabib, A. Bisin, & M. O. Jackson (Eds.), *Handbook of Social Economics* (Vol. 1, pp. 1053–1163). North-Holland. https://doi.org/10.1016/B978-0-444-53707-2.00003-7

Evans, W., & Fitzgerald, D. (2017). *The Economic and Social Outcomes of Refugees in the United States: Evidence from the ACS* (No. w23498; p. w23498). National Bureau of Economic Research. https://doi.org/10.3386/w23498

Fazel, M., Reed, R. V., Panter-Brick, C., & Stein, A. (2012). Mental health of displaced and refugee children resettled in high-income countries: Risk and protective factors. *Lancet (London, England)*, *379*(9812), 266–282. https://doi.org/10.1016/S0140-6736(11)60051-2

Felfe, C., Rainer, H., & Saurer, J. (2019). Why Birthright Citizenship Matters for Immigrant Children: Short- and Long-Run Impacts on Educational Integration. *Journal of Labor Economics*. https://doi.org/10.1086/704570

Figlio, D. N., Giuliano, P., Marchingiglio, R., Özek, U., & Sapienza, P. (2021). *Diversity in Schools: Immigrants and the Educational Performance of U.S. Born Students* (No. w28596). National Bureau of Economic Research. https://doi.org/10.3386/w28596

Figlio, D., & Özek, U. (2019). Unwelcome Guests? The Effects of Refugees on the Educational Outcomes of Incumbent Students. *Journal of Labor Economics*, *37*(4), 36.

Fix, M., Hooper, K., & Zong, J. (2017, June 5). *How Are Refugees Faring? Integration at U.S. and State Levels*. Migrationpolicy.Org. https://www.migrationpolicy.org/research/how-are-refugees-faring-integration-us-and-state-levels

Frattini, T., & Meschi, E. (2017). The Effect of Immigrant Peers in Vocational Schools. *IZA Discussion Papers, No. 11027*.

Gould, E. D., Lavy, V., & Daniele Paserman, M. (2009). Does Immigration Affect the Long-Term Educational Outcomes of Natives? Quasi-Experimental Evidence. *The Economic Journal*, *119*(540), 1243–1269. https://doi.org/10.1111/j.1468-0297.2009.02271.x

Green, C., & Iversen, J. M. V. (2020). Refugees and the Educational Attainment of Natives. *IZA Discussion Paper No. 13433*, 36.

Hoxby, C. M., & Weingarth, G. (2006). *Taking Race Out of the Equation: School Reassignment and the Structure of Peer Effects*.

Hunt, J. (2017). The Impact of Immigration on the Educational Attainment of Natives. *Journal of Human Resources*, *52*(4), 1060–1118. https://doi.org/10.3368/jhr.52.4.0115-6913R1

Imberman, S. A., Kugler, A. D., & Sacerdote, B. I. (2012). Katrina's Children: Evidence on the Structure of Peer Effects from Hurricane Evacuees. *The American Economic Review*, *102*(5), 2048–2082.

Jackson, O. (2015). Does Immigration Crowd Natives Into or Out of Higher Education? *Research Department Working Papers. Federal Reserve Bank of Boston*. https://www.bostonfed.org/publications/research-department-working-paper/2015/does-immigration-crowd-natives-into-or-out-of-higher-education.aspx

Jensen, P., & Rasmussen, A. W. (2011). The effect of immigrant concentration in schools on native and immigrant children's reading and math skills. *Economics of Education Review*, *30*(6), 1503–1515. https://doi.org/10.1016/j.econedurev.2011.08.002

Koedel, C., Mihaly, K., & Rockoff, J. E. (2015). Value-added modeling: A review. *Economics of Education Review*, *47*, 180–195. https://doi.org/10.1016/j.econedurev.2015.01.006

Lavy, V., & Schlosser, A. (2011). Mechanisms and Impacts of Gender Peer Effects at School. *American Economic Journal: Applied Economics*, *3*(2), 1–33. https://doi.org/10.1257/app.3.2.1

Lockwood, J. R., & McCaffrey, D. F. (2014). Correcting for Test Score Measurement Error in ANCOVA Models for Estimating Treatment Effects. *Journal of Educational and Behavioral Statistics*, *39*(1), 22–52. https://doi.org/10.3102/1076998613509405

LoPalo, M. (2019). The effects of cash assistance on refugee outcomes. *Journal of Public Economics*, *170*, 27–52. https://doi.org/10.1016/j.jpubeco.2018.11.004

Manski, C. F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies*, *60*(3), 531–542. JSTOR. https://doi.org/10.2307/2298123

Moffitt, R. (2004). Policy Interventions, Low-Level Equilibria, and Social Interactions. In S. Durlauf & P. Young (Eds.), *Social Dynamics*. MIT Press.

Mossaad, N. (2016). *Annual Flow Report Refugees and Asylees: 2014*. Office of Immigration Statistics, Policy Directorate. Homeland Security.

Mossaad, N. (2019). *Annual Flow Report Refugees and Asylees: 2017*. Office of Immigration Statistics, Office of Strategy, Policy & Plans. Homeland Security. https://www.dhs.gov/sites/default/files/publications/Refugees_Asylees_2017.pdf

Murray, T. J. (2016). Public or private? The influence of immigration on native schooling choices in the United States. *Economics of Education Review*, *53*, 268–283. https://doi.org/10.1016/j.econedurev.2016.04.003

Office of Refugee Resettlement, (ORR). (2018). *Annual Report to Congress 2016*. Administration for Children and Families. https://www.acf.hhs.gov/orr/resource/office-of-refugee-resettlement-annual-report-to-congress-2016

Office of Refugee Resettlement, (ORR). (2021). *Annual Report to Congress 2018*. Administration for Children and Families. https://www.acf.hhs.gov/sites/default/files/documents/orr/ARC_FY2018_508_2_28_2021.pdf

Özek, U. (2021). Examining the Educational Spillover Effects of Severe Natural Disasters: The Case of Hurricane Maria. *Journal of Human Resources*, 0520. https://doi.org/10.3368/jhr.58.4.0520-10893R2

Rivkin, S. G., Hanushek, E. A., & Kain, J. F. (2005). Teachers, Schools, and Academic Achievement. *Econometrica*, *73*(2), 417–458. https://doi.org/10.1111/j.1468-0262.2005.00584.x

Rockoff, J. E. (2004). The Impact of Individual Teachers on Student Achievement: Evidence from Panel Data. *The American Economic Review*, *94*(2), 247–252. JSTOR.

Sass, T. R., Semykina, A., & Harris, D. N. (2014). Value-added models and the measurement of teacher productivity. *Economics of Education Review*, *38*, 9–23. https://doi.org/10.1016/j.econedurev.2013.10.003

Schneeweis, N. (2015). Immigrant concentration in schools: Consequences for native and migrant students. *Labour Economics*, *35*, 63–76. https://doi.org/10.1016/j.labeco.2015.03.004

Schwartz, A. E., & Stiefel, L. (2011). Immigrants and inequality in public schools. In G. Duncan & R. Murnane (Eds.), *Whither Opportunity?: Rising Inequality, Schools, and Children's Life Chances*. Russell Sage Foundation.

Steele, J. L., Slater, R. O., Zamarro, G., Miller, T., Li, J., Burkhauser, S., & Bacon, M. (2017). Effects of Dual-Language Immersion Programs on Student Achievement: Evidence from Lottery Data. *American Educational Research Journal*, *54*(1). https://doi.org/10.3102/0002831216634463

Trump, D. J. (2019). *Executive Order on Enhancing State and Local Involvement in Refugee Resettlement*. https://www.whitehouse.gov/presidential-actions/executive-order-enhancing-state-local-involvement-refugee-resettlement/

Tumen, S. (2019). Refugees and "Native Flight" from Public to Private Schools. *IZA Discussion Paper No. 12235*. https://www.iza.org/publications/dp/12235/refugees-and-native-flight-from-public-to-private-schools

UNHCR. (2020). *Global Trends: Forced Displacement in 2019*. United National High Comissioner for Reugees. https://www.unhcr.org/5ee200e37.pdf

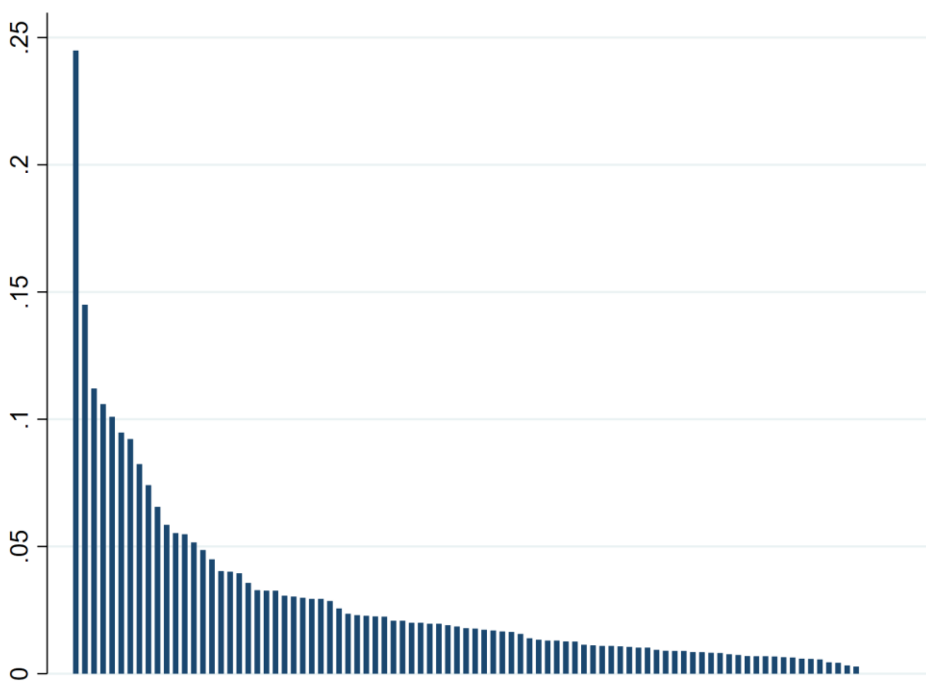
van der Werf, C. (2021). *The Impact of Refugees on Native Students' Academic Achievement*. Working Paper.

Figures and Tables

Figure 1: Georgia Annual Refugee Arrivals (2002-2017)

Source: U.S. Refugee Processing Center

Figure 2: Maximum Variation in the Share of Grade-Level Refugees, All Refugee-Serving Schools



Note: Each bar represents the maximum change in the share of refugee students across grades within a school. There is one bar per school. The sample includes all refugee-serving schools.

Table 1: Summary Statistics by Student Nativity Status, Grades 3-8 (2008-2017)

	U.S. Born		Foreign Born			
			Immigrant		Refugee	
	Mean	SD	Mean	SD	Mean	SD
Achievement						
Normalized ELA Score	-0.21	1.01	-0.33	1.12	-1.25	1.03
Normalized Math Score	-0.27	0.95	-0.21	1.06	-0.93	0.90
Absenteeism						
Days Enrolled	167.89	28.10	164.66	32.78	157.82	38.99
Share days Absent	0.03	0.04	0.03	0.04	0.03	0.05
Chronically Absent	0.07	0.26	0.05	0.22	0.07	0.26
Discipline						
Number of Disciplinary Incidents	0.49	1.57	0.29	1.12	0.20	0.97
Serious Disciplinary Incident	0.17	0.38	0.12	0.33	0.08	0.27
Fighting Incident	0.09	0.28	0.05	0.21	0.04	0.20
Demographics						
Female	0.49	0.50	0.48	0.50	0.48	0.50
Hispanic	0.12	0.32	0.44	0.50	0.03	0.16
Black	0.73	0.44	0.27	0.45	0.30	0.46
White	0.14	0.35	0.16	0.36	0.07	0.25
Asian	0.03	0.16	0.22	0.41	0.62	0.49
Special Ed	0.09	0.29	0.05	0.22	0.02	0.14
Gifted	0.17	0.37	0.11	0.32	0.01	0.12
FRL	0.71	0.46	0.79	0.41	0.89	0.31
Current EL	0.05	0.21	0.42	0.49	0.84	0.37
Ever EL	0.08	0.28	0.61	0.49	0.98	0.13
Observations	396,560		29,546		12,737	

Note: Mean and standard deviation of variables used in the regressions are shown by nativity status. Refugee students are identified using the self-reported measure, excluding students who self-report as born in the US. “Immigrant” refers to all foreign-born students who do not self-report as refugees. Nativity status is based on the country of birth reported in the first year that students appear in the data.

Table 2: ELA Achievement of Non-Refugee Students (Grades 4 – 8): Linear-in-Means Refugee Peer Effects

	(1)	(2)	(3)
	All	US Born	Immigrant
VARIABLES			
Panel A: All refugee-serving schools			
Share of grade-level refugees	0.102	0.126	-0.095
	(0.216)	(0.224)	(0.495)
Obs.	239,789	223,770	16,019
Panel B: Refugee-serving schools above 1 % concentration			
Share of grade-level refugees	-0.030	-0.026	-0.033
	(0.247)	(0.256)	(0.457)
Obs.	44,772	40,379	4,393
School-Year FE	X	X	X
Grade FE	X	X	X
Demographic controls	X	X	X
Lagged test score	X	X	X

Note: Refugee students are identified using the self-reported measure, excluding students who self-report as born in the US. Column (1) reports estimates using the full sample of all non-refugee students. Columns (2) and (3) report estimates using the US Born and Immigrant sub-samples, respectively. ELA test scores are normalized to zero mean and unit variance with respect to the state-wide test score distribution by year-subject-grade. Demographic controls include indicators for race, gender, free and reduced-price lunch eligibility, and participation in ESL and special education services. Robust standard errors clustered at the school-year-grade level are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Math Achievement of Non-Refugee Students (Grades 4 – 8): Linear-in-Means Refugee Peer Effects

	(1)	(2)	(3)
	All	US Born	Immigrant
VARIABLES			
Panel A: All refugee-serving schools			
Share of grade-level refugees	0.603	0.662	0.311
	(0.401)	(0.429)	(0.428)
Obs.	238,920	222,035	16,885
Panel B: Refugee-serving schools above 1 % concentration			
Share of grade-level refugees	1.002**	1.041**	0.855*
	(0.412)	(0.443)	(0.470)
Obs.	44,800	40,056	4,744
School-Year FE	X	X	X
Grade FE	X	X	X
Demographic controls	X	X	X
Lagged test score	X	X	X

Note: Refugee students are identified using the self-reported measure, excluding students who self-report as born in the US. Column (1) reports estimates using the full sample of all non-refugee students. Columns (2) and (3) report estimates using the US Born and Immigrant sub-samples, respectively. Math test scores are normalized to zero mean and unit variance with respect to the state-wide test score distribution by year-subject-grade. Demographic controls include indicators for race, gender, free and reduced-price lunch eligibility, and participation in ESL and special education services. Robust standard errors clustered at the school-year-grade level are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: ELA Achievement of Non-Refugee Students (Grades 4 – 8): Nonlinear-in-Means Refugee Peer Effects

	(1)	(2)	(3)
	All	US Born	Immigrant
VARIABLES			
Panel A: All refugee-serving schools			
Share of grade-level refugees × low achievement	-0.405*	-0.422*	-0.382
	(0.225)	(0.235)	(0.502)
Share of grade-level refugees × mid achievement	0.070	0.081	0.036
	(0.220)	(0.228)	(0.506)
Share of grade-level refugees × high achievement	0.930***	0.990***	0.496
	(0.232)	(0.241)	(0.514)
Obs.	239,789	223,770	16,019
Panel B: Refugee-serving schools above 1 % concentration			
Share of grade-level refugees × low achievement	-0.576**	-0.615**	-0.303
	(0.256)	(0.266)	(0.461)
Share of grade-level refugees × mid achievement	-0.025	-0.041	0.103
	(0.249)	(0.259)	(0.459)
Share of grade-level refugees × high achievement	0.840***	0.883***	0.477
	(0.258)	(0.269)	(0.480)
Obs.	44,772	40,379	4,393
School-Year FE	X	X	X
Grade FE	X	X	X
Demographic controls	X	X	X
Lagged test score	X	X	X

Note: Refugee students are identified using the self-reported measure, excluding students who self-report as born in the US. Column (1) reports estimates using the full sample of all non-refugee students. Columns (2) and (3) report estimates using the US Born and Immigrant sub-samples, respectively. ELA test scores are normalized to zero mean and unit variance with respect to the state-wide test score distribution by year-subject-grade. Students are classified into "low", "high", or "middle" initial achievement based on whether their first-observed ELA test score falls in the bottom quintile, highest quintile, or middle quintiles of the state-wide distribution. Demographic controls include indicators for race, gender, free and reduced-price lunch eligibility, and participation in ESL and special education services. Robust standard errors clustered at the school-year-grade level are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Math Achievement of Non-Refugee Students (Grades 4 – 8): Nonlinear-in-Means Refugee Peer Effects

	(1)	(2)	(3)
	All	US Born	Immigrant
VARIABLES			
Panel A: All refugee-serving schools			
Share of grade-level refugees × low achievement	0.288	0.283	0.143
	(0.411)	(0.438)	(0.439)
Share of grade-level refugees × mid achievement	0.513	0.584	0.224
	(0.401)	(0.428)	(0.434)
Share of grade-level refugees × high achievement	1.402***	1.509***	0.949**
	(0.404)	(0.431)	(0.454)
Obs.	238,920	222,035	16,885
Panel B: Refugee-serving schools above 1 % concentration			
Share of grade-level refugees × low achievement	0.632	0.624	0.663
	(0.417)	(0.446)	(0.474)
Share of grade-level refugees × mid achievement	0.954**	1.002**	0.785
	(0.411)	(0.441)	(0.478)
Share of grade-level refugees × high achievement	1.855***	1.928***	1.507***
	(0.420)	(0.450)	(0.506)
Obs.	44,800	40,056	4,744
School-Year FE	X	X	X
Grade FE	X	X	X
Demographic controls	X	X	X
Lagged test score	X	X	X

Note: Refugee students are identified using the self-reported measure, excluding students who self-report as born in the US. Column (1) reports estimates using the full sample of all non-refugee students. Columns (2) and (3) report estimates using the US Born and Immigrant sub-samples, respectively. Math test scores are normalized to zero mean and unit variance with respect to the state-wide test score distribution by year-subject-grade. Students are classified into “low”, “high”, or “middle” initial achievement based on whether their first-observed math test score falls in the bottom quintile, highest quintile, or middle quintiles of the state-wide distribution. Demographic controls include indicators for race, gender, free and reduced-price lunch eligibility, and participation in ESL and special education services. Robust standard errors clustered at the school-year-grade level are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 6: ELA and Math Achievement of Non-Refugee Students (Grades 4 – 8): Heterogeneous Effects by Refugee EL Status

VARIABLES	(1) ELA	(2) Math
Panel A: All refugee-serving schools		
Share of EL grade-level refugees	0.174	0.784*
	(0.238)	(0.424)
Share of non-EL grade-level refugees	-0.185	-0.132
	(0.357)	(0.681)
Obs.	239,789	238,920
Panel B: Refugee-serving schools above 1 % concentration		
Share of EL grade-level refugees	0.039	1.175***
	(0.261)	(0.433)
Share of non-EL grade-level refugees	-0.413	0.046
	(0.407)	(0.738)
Obs.	44,772	44,800
School-Year FE	X	X
Grade FE	X	X
Demographic controls	X	X
Lagged test score	X	X

Note: Refugee students are identified using the self-reported measure, excluding students who self-report as born in the US. EL status of refugees is determined based on whether the student receives ESL services. Column (1) reports estimates using the full sample of all non-refugee students using ELA test scores as the outcome variable. Column (2) reports estimates using the full sample of all non-refugee students using math test scores as the outcome variable. ELA and math test scores are normalized to zero mean and unit variance with respect to the state-wide test score distribution by year-subject-grade. Demographic controls include indicators for race, gender, free and reduced-price lunch eligibility, and participation in ESL and special education services. Robust standard errors clustered at the school-year-grade level are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 7: ELA and Math Achievement of Non-Refugee Students (Grades 4 – 8): Heterogeneous Effects by Refugees Length of Stay, Up to 5 Years Post Arrival

VARIABLES	(1) ELA	(2) Math
Panel A: All refugee-serving schools		
Share of grade-level refugees, up to 5 years	0.100	0.753*
	(0.225)	(0.420)
Share of grade-level refugees, 6+ years	0.109	0.080
	(0.301)	(0.507)
Obs.	239,789	238,920
Panel B: Refugee-serving schools above 1 % concentration		
Share of grade-level refugees, up to 5 years	-0.002	1.331***
	(0.257)	(0.426)
Share of grade-level refugees, 6+ years	-0.141	-0.279
	(0.343)	(0.549)
Obs.	44,772	44,800
School-Year FE	X	X
Grade FE	X	X
Demographic controls	X	X
Lagged test score	X	X

Note: Refugee students are identified using the self-reported measure, excluding students who self-report as born in the US. Column (1) reports estimates using the full sample of all non-refugee students using ELA test scores as the outcome variable. Column (2) reports estimates using the full sample of all non-refugee students using math test scores as the outcome variable. ELA and math test scores are normalized to zero mean and unit variance with respect to the state-wide test score distribution by year-subject-grade. Demographic controls include indicators for race, gender, free and reduced-price lunch eligibility, and participation in ESL and special education services. Robust standard errors clustered at the school-year-grade level are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

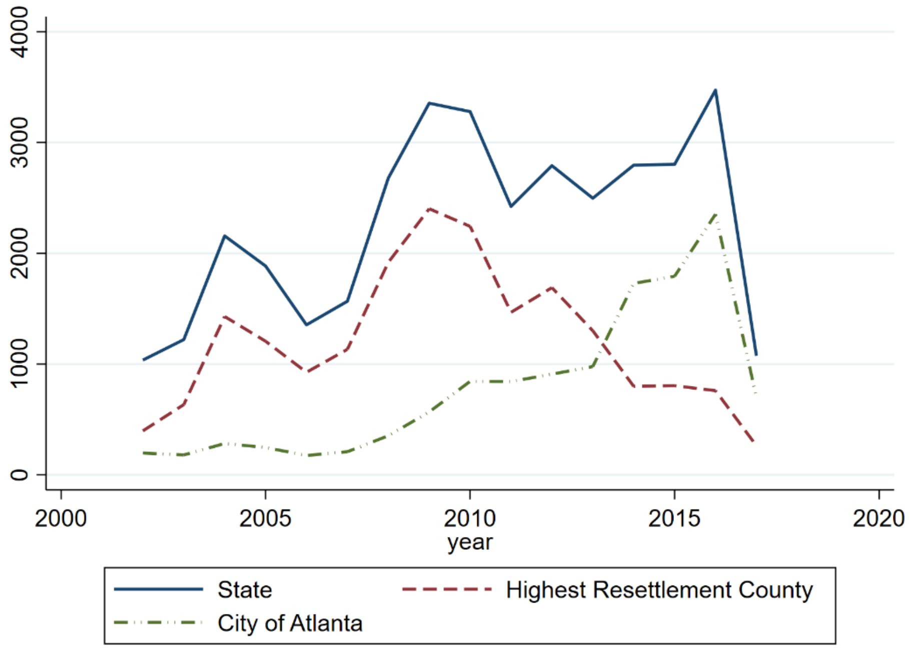
Table 8: ELA and Math Achievement of Non-Refugee Students (Grades 4 – 8): Robustness Checks

	Include "Refugees" Born in US		Use Variation in Same-Year Refugee Arrivals		Redefine School Type over Grades 3-8		Drop School with Highest Variation		Add Grade-by-Year FEs		Add Grade-by-School FEs		Add Grade-by School and Grade-by-Year FEs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
VARIABLES	ELA	Math	ELA	Math	ELA	Math	ELA	Math	ELA	Math	ELA	Math	ELA	Math
Panel A: All refugee-serving schools														
Share of grade-level refugees	0.092	0.641	-0.159	-0.647	0.109	0.615	0.013	0.625	0.077	0.545*	-0.172	0.737**	-0.207	0.595**
	(0.215)	(0.400)	(0.711)	(0.989)	(0.216)	(0.401)	(0.215)	(0.399)	(0.200)	(0.314)	(0.209)	(0.348)	(0.201)	(0.274)
Obs.	242,295	241,425	239,789	238,920	232,245	231,392	239,080	238,195	239,789	238,920	239,789	238,920	239,789	238,920
Panel B: Refugee-serving schools above 1 % concentration														
Share of grade-level refugees	-0.089	1.112***	-0.568	0.151	-0.002	1.042**	-0.176	0.937**	-0.118	0.913***	-0.118	0.824**	-0.235	0.708**
	(0.247)	(0.414)	(0.714)	(0.979)	(0.241)	(0.404)	(0.239)	(0.434)	(0.255)	(0.341)	(0.225)	(0.373)	(0.236)	(0.307)
Obs.	44,607	44,627	44,772	44,800	50,530	50,536	44,063	44,075	44,772	44,800	44,772	44,800	44,772	44,800
School-Year FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Grade FE	X	X	X	X	X	X	X	X						
Demo controls	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Lagged test score	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Grade-Year FE									X	X			X	X
Grade-School FE											X	X	X	X

Note: Refugee students are identified using the self-reported measure, excluding students who self-report as born in the US. All point estimates are from regressions using the pooled sample of US-born and immigrant students. Odd-numbered columns report estimates using ELA test scores as the outcome variable. Even-numbered columns report estimates using math test scores as the outcome variable. ELA and math test scores are normalized to zero mean and unit variance with respect to the state-wide test score distribution by year-subject-grade. Demographic controls include indicators for race, gender, free and reduced-price lunch eligibility, and participation in ESL and special education services. Robust standard errors clustered at the school-year-grade level are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Appendix A: Additional Figures and Tables

Figure A.1: Georgia Annual Refugee Arrivals by Destination County or City (2002-2017)



Source: U.S. Refugee Processing Center

Table A.1: Summary Statistics of Non-Refugee Students by School Type, Grades 3-8 (2008-2017)

	No Refugee Serving Schools		All Refugee-Serving Schools		Refugee Serving Schools above 1 Percent	
	Mean	SD	Mean	SD	Mean	SD
Total Refugee Students per Grade			5.24	17.46	24.81	33.10
Share Refugee Students per Grade			0.02	0.07	0.11	0.13
Achievement						
Normalized ELA Score	-0.22	1.02	-0.22	1.01	-0.32	0.99
Normalized Math Score	-0.32	0.93	-0.26	0.96	-0.36	0.90
Absenteeism						
Days Enrolled	168.75	27.00	167.51	28.66	165.11	31.44
Share days Absent	0.03	0.04	0.03	0.04	0.04	0.04
Chronically Absent	0.06	0.25	0.07	0.26	0.08	0.28
Discipline						
Number of Disciplinary Incidents	0.36	1.38	0.49	1.56	0.59	1.72
Serious Disciplinary Incident	0.12	0.33	0.17	0.38	0.20	0.40
Fighting Incident	0.07	0.25	0.09	0.28	0.10	0.30
Demographics						
Female	0.49	0.50	0.49	0.50	0.48	0.50
Hispanic	0.05	0.22	0.15	0.36	0.12	0.33
Black	0.85	0.36	0.68	0.47	0.70	0.46
White	0.10	0.30	0.15	0.35	0.14	0.35
Asian	0.01	0.11	0.04	0.20	0.07	0.26
Special Ed	0.09	0.28	0.09	0.29	0.10	0.30
Gifted	0.16	0.37	0.16	0.37	0.11	0.32
FRL	0.68	0.47	0.72	0.45	0.80	0.40
Current EL	0.02	0.15	0.08	0.27	0.11	0.31
Ever EL	0.04	0.18	0.13	0.34	0.16	0.37
No. of Schools	15		109		21	
Observations	52,582		373,524		72,267	

Note: Sample of all non-refugee peers. I determined school type based on the mean proportion of refugee students over the sample period and across all grades. By construction, the total and share of refugees by grade in schools that never serve refugees is zero.

Table A.2: ELA and Math Achievement of Non-Refugee Students (Grades 4 – 8): Heterogeneous Effects by Refugees Length of Stay, Recently Arrived

VARIABLES	(1) ELA	(2) Math
Panel A: All refugee-serving schools		
Share of grade-level refugees, recently arrived	-0.139	-0.523
	(0.717)	(1.040)
Share of grade-level refugees, settled	0.120	0.687*
	(0.225)	(0.408)
Obs.	239,789	238,920
Panel B: Refugee-serving schools above 1 % concentration		
Share of grade-level refugees, recently arrived	-0.566	0.508
	(0.717)	(1.014)
Share of grade-level refugees, settled	0.006	1.035**
	(0.253)	(0.425)
Obs.	44,772	44,800
School-Year FE	X	X
Grade FE	X	X
Demographic controls	X	X
Lagged test score	X	X

Note: Refugee students are identified using the self-reported measure, excluding students who self-report as born in the US. Recently arrived refugees are defined as those whose year of arrival is the same as the school year, i.e., those with less than 1 year since arrival. Settled refugees are defined as those with 1 or more years since arrival. Column (1) reports estimates using the full sample of all non-refugee students and ELA test scores as the outcome variable. Column (2) reports estimates using the full sample of all non-refugee students and math test scores as the outcome variable. ELA and math test scores are normalized to zero mean and unit variance with respect to the state-wide test score distribution by year-subject-grade. Demographic controls include indicators for race, gender, free and reduced-price lunch eligibility, and participation in ESL and special education services. Robust standard errors clustered at the school-year-grade level are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A.3: ELA and Math Achievement of Non-Refugee Students (Grades 4 – 8): Heterogeneous Effects by Non-refugee EL Status

VARIABLES	(1) ELA	(2) Math
Panel A: All refugee-serving schools		
Share of grade-level refugees	0.109	0.594
	(0.216)	(0.401)
Share of grade-level refugees × ESL	-0.099	0.109
	(0.070)	(0.080)
Obs.	239,789	238,920
Panel B: Refugee-serving schools above 1 % concentration		
Share of grade-level refugees	-0.013	1.008**
	(0.247)	(0.413)
Share of grade-level refugees × ESL	-0.217**	-0.070
	(0.085)	(0.090)
Obs.	44,772	44,800
School-Year FE	X	X
Grade FE	X	X
Demographic controls	X	X
Lagged test score	X	X

Note: Refugee students are identified using the self-reported measure, excluding students who self-report as born in the US. EL status of non-refugees is determined based on whether the student receives ESL services. Column (1) reports estimates using the full sample of all non-refugee students and ELA test scores as the outcome variable. Column (2) reports estimates using the full sample of all non-refugee students and math test scores as the outcome variable. ELA and math test scores are normalized to zero mean and unit variance with respect to the state-wide test score distribution by year-subject-grade. Demographic controls include indicators for race, gender, free and reduced-price lunch eligibility, and participation in ESL and special education services. Robust standard errors clustered at the school-year-grade level are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A.4: ELA and Math Achievement of Non-Refugee Students (Grades 4 – 8): Heterogeneous Effects by Grade Levels

VARIABLES	(1) ELA	(2) Math
Panel A: All refugee-serving schools		
Elementary Schools		
Share of Grade-Level Refugees	0.151	0.190
	(0.312)	(0.456)
Obs.	88,714	88,960
Middle Schools		
Share of Grade-Level Refugees	-0.023	0.995
	(0.315)	(0.664)
Obs.	140,642	139,664
Panel B: Refugee-serving schools above 1% concentration		
Elementary Schools		
Share of Grade-Level Refugees	0.143	0.503
	(0.341)	(0.415)
Obs. too	14,897	15,082
Middle Schools		
Share of Grade-Level Refugees	-0.248	1.608**
	(0.353)	(0.730)
Obs.	29,875	29,718
School-Year FE	X	X
Grade FE	X	X
Demographic controls	X	X
Lagged test score	X	X

Note: Refugee students are identified using the self-reported measure, excluding students who self-report as born in the US. Elementary Schools are classified as schools serving grades K-5 exclusively. Middle Schools are classified as school serving grades 6-8 exclusively. Column (1) reports estimates using the full sample of all non-refugee students and ELA test scores as the outcome variable. Column (2) reports estimates using the full sample of all non-refugee students and math test scores as the outcome variable. ELA and math test scores are normalized to zero mean and unit variance with respect to the state-wide test score distribution by year-subject-grade. Demographic controls include indicators for race, gender, free and reduced-price lunch eligibility, and participation in ESL and special education services. Robust standard errors clustered at the school-year-grade level are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A.5: ELA and Math Achievement of Non-Refugee Students (Grades 4 – 8): Additional Robustness Checks

	Cluster Errors at School-Year Level		Cluster Errors at School-Level		Control for ELA and Math Lagged Scores		Exclude SY 2015		Use Change in Norm. Test Score as Outcome Variable	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	ELA	Math	ELA	Math	ELA	Math	ELA	Math	ELA	Math
Panel A: All refugee-serving schools										
Share of grade-level refugees	0.102	0.603	0.102	0.603	0.055	0.542	0.098	0.257	-0.122	0.427
	(0.274)	(0.517)	(0.262)	(0.472)	(0.218)	(0.403)	(0.236)	(0.380)	(0.250)	(0.439)
Obs.	239,789	238,920	239,789	238,920	239,136	237,506	213,883	213,005	239,789	238,920
Panel B: Refugee-serving schools above 1 % concentration										
Share of grade-level refugees	-0.030	1.002**	-0.030	1.002	-0.043	0.975**	-0.038	0.724*	-0.124	0.910**
	(0.309)	(0.505)	(0.296)	(0.607)	(0.247)	(0.412)	(0.268)	(0.386)	(0.278)	(0.444)
Obs.	44,772	44,800	44,772	44,800	44,627	44,348	40,243	40,265	44,772	44,800
School-Year FE	X	X	X	X	X	X	X	X	X	X
Grade FE	X	X	X	X	X	X	X	X	X	X
Demographic controls	X	X	X	X	X	X	X	X	X	X
Lagged test score	X	X	X	X	X	X	X	X		

Note: Refugee students are identified using the self-reported measure, excluding students who self-report as born in the US. All point estimates are from regressions using the pooled sample of US-born and immigrant students. Odd-numbered columns report estimates using ELA test scores as the outcome variable. Even-numbered columns report estimates using math test scores as the outcome variable. ELA and math test scores are normalized to zero mean and unit variance with respect to the state-wide test score distribution by year-subject-grade. Demographic controls include indicators for race, gender, free and reduced-price lunch eligibility, and participation in ESL and special education services. Unless stated in column title, robust standard errors clustered at the school-year-grade level are shown in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.6: ELA Achievement of Non-Refugee Students (Grades 4 – 8): Heterogeneous Effects by Nonlinearities in the Share of Refugees

VARIABLES	(1) ELA	(2) ELA
Panel A: All refugee-serving schools		
Share of grade-level refugees	0.087	-0.000
	(0.354)	(0.314)
Square of Share of grade-level refugees	0.045	
	(0.623)	
Share of grade-level refugees × Total school-level refugees		0.001
		(0.001)
Obs.	239,789	239,789
Panel B: Refugee-serving schools above 1 % concentration		
Share of grade-level refugees	-0.010	-0.066
	(0.419)	(0.370)
Square of Share of grade-level refugees	-0.052	
	(0.672)	
Share of grade-level refugees × Total school-level refugees		0.000
		(0.001)
Obs.	44,772	44,772
School-Year FE	X	X
Grade FE	X	X
Demographic controls	X	X
Lagged test score	X	X

Note: Refugee students are identified using the self-reported measure, excluding students who self-report as born in the US. All columns report estimates from separate regressions using the full sample of all non-refugee students and ELA test scores as the outcome variable. ELA test scores are normalized to zero mean and unit variance with respect to the state-wide test score distribution by year-subject-grade. Demographic controls include indicators for race, gender, free and reduced-price lunch eligibility, and participation in ESL and special education services. Robust standard errors clustered at the school-year-grade level are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A.7: Math Achievement of Non-Refugee Students (Grades 4 – 8): Heterogeneous Effects by Nonlinearities in the Share of Refugees

VARIABLES	(1) Math	(2) Math
Panel A: All refugee-serving schools		
Share of grade-level refugees	-0.133	-0.383
	(0.565)	(0.516)
Square of Share of grade-level refugees	2.074*	
	(1.211)	
Share of grade-level refugees × Total school-level refugees		0.006***
		(0.002)
Obs.	238,920	238,920
Panel B: Refugee-serving schools above 1 % concentration		
Share of grade-level refugees	-0.058	-0.281
	(0.619)	(0.547)
Square of Share of grade-level refugees	2.665**	
	(1.311)	
Share of grade-level refugees × Total school-level refugees		0.008***
		(0.002)
Obs.	44,800	44,800
School-Year FE	X	X
Grade FE	X	X
Demographic controls	X	X
Lagged test score	X	X

Note: Refugee students are identified using the self-reported measure, excluding students who self-report as born in the US. All columns report estimates from separate regressions using the full sample of all non-refugee students and math test scores as the outcome variable. Math test scores are normalized to zero mean and unit variance with respect to the state-wide test score distribution by year-subject-grade. Demographic controls include indicators for race, gender, free and reduced-price lunch eligibility, and participation in ESL and special education services. Robust standard errors clustered at the school-year-grade level are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Appendix B: Note on the Identification of Refugee Students

I identify refugee students using data on a self-reported measure of refugee status, allowing me to distinguish between refugees and other foreign-born students directly. While this is the preferred measure, I also explore a second strategy commonly used in the literature (see Cortes 2004, Capps et al. 2015, and Evans and Fitzgerald 2017) to account for possible self-selection arising from voluntary identification as refugees.

This alternative method uses publicly available data on refugee arrivals by year and country of birth to determine whether a foreign-born individual is a refugee. I access city-level data on refugee arrival flows from the Refugee Processing Center (RPC) and construct country-year pairs that indicate the countries from which refugees in Georgia arrived in a particular year. I use this list to identify potential refugee students based on their country of birth. The *potential refugee* student population in my data includes all foreign-born students whose country of origin is on the annual refugee arrivals list within the five years prior to being first observed as a public school student.[46]

The main known source of potential bias in the proxy approach is the likelihood to overcount refugees, especially those who come from countries with a relatively high number of immigrants. There are modified approaches that minimize this issue by restricting the list of likely refugee countries to those with a high refugee-to-foreign-born ratio (see Evans and Fitzgerald 2017 for an example of this approach). To my knowledge, and largely due to data limitations, there has not been a direct assessment of the extent of overcounting that arises from using the proxy approach. Because of the unique data that I use for this paper, I can directly

[46] I allow for a 5-year window to account for the possibility that refugees may arrive as infants and first appear in school records up to 5 years after their arrival. Due to the high annual flow of refugees, most countries do not rely on the 5-year window to be included on the list.

assess the validity of the proxy measure against a self-reported identifier using a longitudinal, administrative data set.

Figure B.1 plots the total refugee counts by the self-reported and proxy measures for a select group of countries to illustrate examples of the differences between the two approaches. A comparison between the two measures reveals that, in addition to overcounting refugees from countries with high immigration, the proxy approach also fails to account for refugees whose country of birth is not on the official list of refugee arrivals to the United States. For example, the proxy measure identifies virtually no refugees from Nepal or Thailand directly from the fact that, in the RPC data, no refugees arrived in the state of Georgia from these countries.[47] However, the self-reported data shows that close to 1,300 refugee students come from these countries. A close investigation into these differences revealed two important facts that helped reconcile these discrepancies. First, none of the self-reported refugees from Thailand or Nepal reported speaking a language commonly spoken in these countries. Instead, they report speaking languages from other refugee-sending countries. Second, both of these countries host large refugee camps, some of which had direct resettlement programs with the United States.[48] Thus, there is evidence to conclude that the self-reported refugees who are not identified using the proxy approach are "true" refugees, likely arriving from camps in transient countries, not students misreporting their refugee status.[49]

The results presented in the current version of the paper include only those that utilize the self-reported measure to define refugee students, as it provides a more accurate representation of

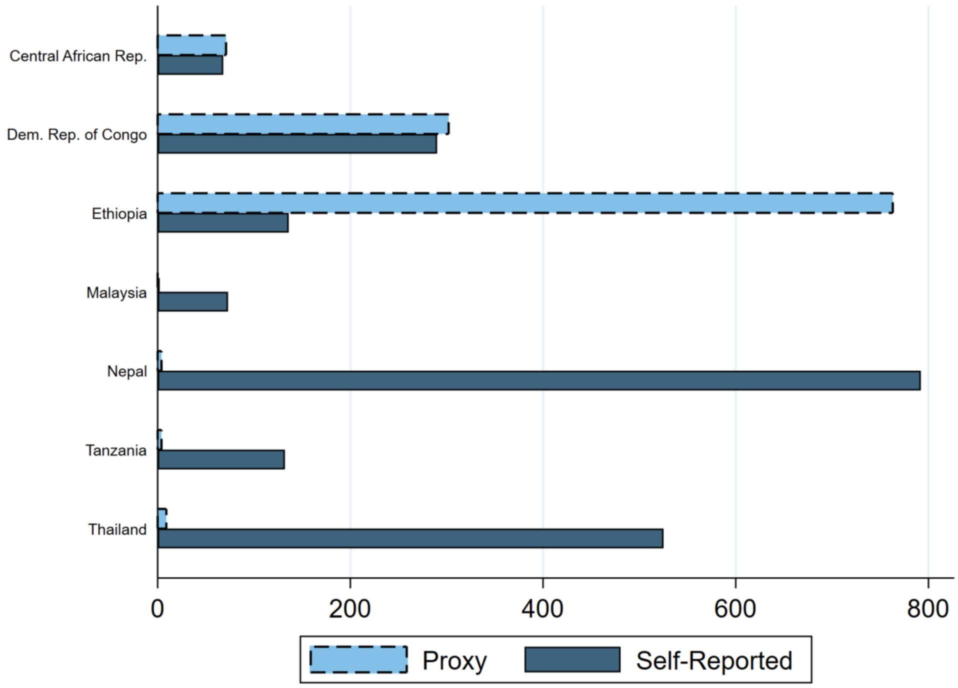
---

[47] I highlight these two countries because they are the ones with the greatest undercounts of refugees. Other countries include Tanzania, Malaysia, and Kenya.
[48] https://www.unhcr.org/en-us/news/latest/2014/1/52e90f8f6/wraps-group-resettlement-myanmar-refugees-thailand.html
[49] I also consulted school administrators and program managers working for refugee-serving organizations in Georgia, who confirmed that many refugees who arrive from camps are likely to mark their "camp country" as their place of birth even if they do not have citizenship from that country.

the refugee student population in the sample district. It is important to note, however, that results are sensitive to whether I define refugees using the proxy or self-reported measure. This is, in part, driven by differences in achievement and sociodemographic characteristics. Self-reported refugees have significantly lower test scores and are more likely to be low income and English Learners. Using the proxy method to identify refugees, I find that an increase in the share of refugee students in a grade leads to positive spillovers in ELA and no effect in math. Notably, neither refugee specification shows negative average spillovers in achievement.[50]

[50] Results using the proxy method to identify refugees can be made available upon request.

Figure B.1: Comparison between Proxy and Self-Reported Counts, Select Countries



Note: Count of refugee students by identification methodology. "Proxy" identifies refugees using country of birth and year or arrival matched to aggregate counts of refugee arrivals to Georgia by country of birth and year of arrival. Self-reported refugees are identified using the self-reported information obtained through the district's International Welcome Center. Only a select group of countries are shown to depict differences between identification methodologies.